Adapting Data Fusion Frameworks

for Condition Based Maintenance

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ABSTRACT

The term *data fusion* is a relatively new term to the condition monitoring community. In defence and other applications the field is mature and has seen extensive application. A corresponding theoretical advance has been made in methods and in frameworks for applications. The important advances in terms of condition monitoring include:

- the crystallisation of a cohesive scheme for problem definition;
- structured solution selection;
- comparisons with dissimilar application fields which have similar problem structures or solution methods;
- the blending of quantitative and qualitative methods which have produced encouraging results for CM solutions but are limited when used in isolation.

This paper reviews existing architectures or frameworks, and proposes a new model for data fusion strategy in condition monitoring. Examples are drawn from manufacturing and plant applications.

Keywords: Condition monitoring, data fusion.

INTRODUCTION

Definitions of *data fusion* have been proposed by several authors. Fusion is defined materially as a process of blending, usually with the application of heat to melt constituents together (OED), but in data processing the more abstract form of union or blending together is meant. The “heat” is applied with a series of algorithms which, depending on the technique used, give a more or less abstract relationship between the constituents and the finished output.

A “fused” definition, which fits many examples in engineering, identifies data fusion as the process of combining data and knowledge from different sources with the aim of maximising the useful information content, for improved reliability or discriminant capability, whilst minimising the quantity of data ultimately retained.

Most data fusion users find that the field is wider than they thought. Llinas described data fusion as a “cottage industry” [1]. The field is not simply about the core algorithms, but also about the way the problem is formulated and the choice of methods. The range of applications is vast. Fusion users in widely differing disciplines can shed light on structurally similar problems.

The sensor and signal processing communities have been using fusion to synthesise the results of two or more sensors for some years. This simple step recognises the limitations of a single sensor but exploits the capability of another similar or dissimilar sensor to calibrate, add dimensionality or simply to increase statistical significance or robustness to cope with sensor uncertainty. In many such applications the fusion process is necessary to gain sufficient detail in the required domain.

Crucially for condition monitoring, the encompassing philosophy of data fusion allows us to cross some boundaries where recent applications have faltered:

- it is possible to deal with the selection of data processing methods based on problem characteristics, e.g. data or knowledge density; the relationships are becoming clearer;
- we can merge qualitative and quantitative information, e.g. diagnostics data and expert knowledge, in a probabilistic or possibilistic framework.

There are many problems to be overcome. A number of proposed frameworks exist, and each needs work before it could be called generic. There is much to be learnt from existing methods for technique selection, even if those are heuristic and empirical. Integrated approaches will involve multi-level fusion – sensor data, novelty detection, feature classification, diagnosis and decision making.

STRUCTURES IN DATA FUSION

Several architectures, as structures are commonly called in the data fusion community, has been proposed in the literature. The lay out of these architectures varies in relation to the field of application. In 1984 the US Department of Defence established the Sub-Panel for Data Fusion Joint Directors of Laboratories (JDL) in an effort to consolidate this analytical field among researchers. The architecture developed by JDL [1] assumes a level distribution for the fusion process, characterising the data from the source signal level to a refinement level, where the fusion of information takes place in terms of data association, state estimation or object classification. Situation assessment could then proceed, at a higher level of inference, to fuse the object representations provided by the refinement and draw a course of action. Figure 1 depicts the general JDL model. Without loss of generality, it is obvious that the JDL architecture can be adapted to accommodate the problem at hand.

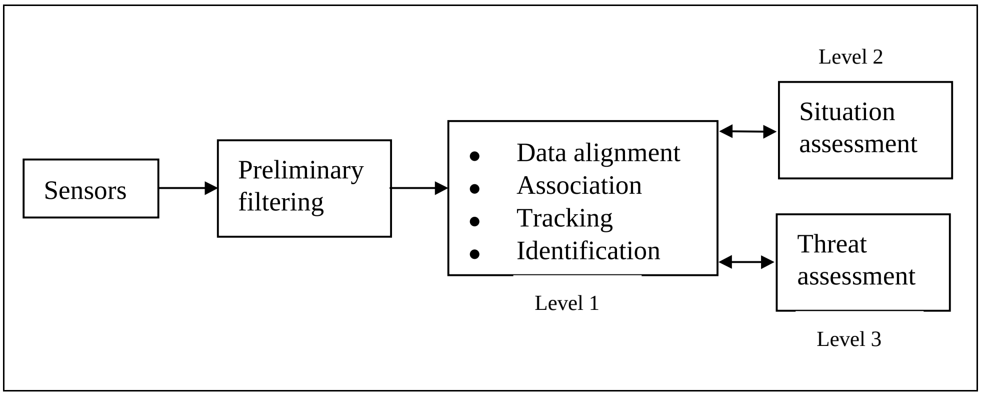


Figure 1: JDL data fusion architecture.

The strategy to implement data fusion varies from one application to the next, but three stages can commonly be identified. Depending on the problem, it is not always necessary to apply all the stages:

- ***Pre-processing***, i.e. reduction of the quantity of data whilst retaining useful information and improving its quality, with minimal loss of detail. The pre-processing may include feature extraction and sensor validation. Some of the techniques used include dimension reduction, gating for association, thresholding, Fourier transform, averaging, and image processing.

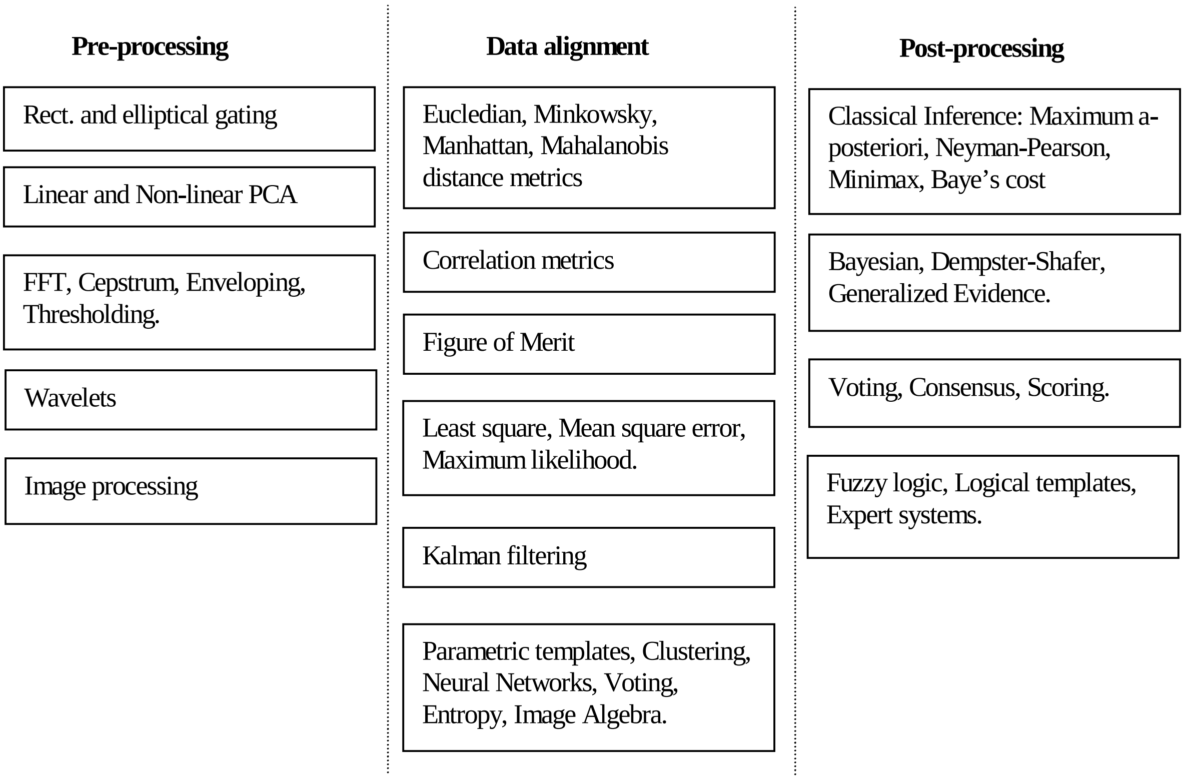


Figure 2: A method map in data fusion.

- ***Data alignment***, where the techniques must fuse the results of multiple independent sensors, or possibly features already extracted in pre-processing. These include association metrics, batch and sequential estimation processes, grouping techniques, and model-based methods.

- ***Post-processing***, combining the mathematical data with knowledge, and decision making. Techniques could be classified as knowledge-based, cognitive-based, heuristic, and statistical.

Figure 2 shows an overview of the aforementioned techniques, which characterise data fusion applications, dividing the domain into three overlapping regions.

Many researchers have focused on specific methods applied to particular problems, or particular aspects of the architecture. Examples include architectural issues dealing with the problem of multiple sensors in similar or dissimilar domains [2-4]. Extended Kalman filtering [5], model based approaches [6-8], wavelet decomposition [9], Artificial Neural Networks [10,11] and Fuzzy Logic [12]. The National Physical Laboratory has provided a review of data fusion to the INTErSECT community [13].

The fusion of data can take place at different levels of representation, namely:

- ***Raw data*** fusion at the signal/pixel level, where the raw data is robustly and redundantly merged or sensors are validated.
- ***Feature*** fusion at the feature level, where a characteristic is extracted before fusion occurs.
- ***Decision*** fusion at the symbol level, where measured data with or without pre-processing is combined with processed data or *a priori* knowledge.

APPLICATIONS OF DATA FUSION

Practical applications of data fusion have necessarily been those areas in which the required output of an analysis may not be measured directly. This is particularly important in medical imaging [6], non-destructive testing [14] and remote sensing, such as target identification and tracking [3,8,10]. The methods are particularly popular in Condition Monitoring, where the purpose is to detect faults and the degradation of machine health [5,7,9,11,12,15,16].

Work at Manchester has pursued a number of methods under the data fusion umbrella. A variety of novel measurement, advanced signal processing and feature extraction techniques are being used in the detection, location, severity assessment and diagnosis of faults:

- Modelling and parameter estimation have been used to analyse diesel fuel injectors, characterising the measured data with wavelet transforms [17];
- Three dimensional measurements are fused from stereoscopic image data for the measurement of robot repeatability, using robust pixel interpolation with the Hough transform [18];
- Gear faults are diagnosed and located using classical vibration analysis, cepstrum and wavelet transforms [19];
- Neural networks have been applied to a variety of applications including diesel cylinder pressure reconstruction [20];
- Linear and non-linear System Identification is extensively used in structural analysis for aerospace applications [21];
- Optimisation in control and aerospace applications have utilised parameter estimation, fuzzy logic, neural networks and statistical methods [22-24].

This range of applications has led to a deep understanding of particular techniques but moreover a comprehension of the differing architectures of problem solution configurations and their unique characteristics.

A CONDITION MONITORING PERSPECTIVE

Data Fusion has rooted applications in the field of Condition monitoring due to the fact that large amount of data should be processed if proper assessment of the machine's health is to be ensured. The inspection of the machine could be performed on-line, in a continuous fashion, or off-line, on a scheduled basis. The data would then be processed in a sequential or in a batch manner, respectively. The data arriving to the fusion centre contain vibration, temperature, pressure, oil analysis, and other measurements that encapsulates the parametric properties of the system and can aid in its condition assessment.

An important aspect of condition monitoring is the fidelity of information received by the sensor units. The data acquired must be consistent and as much noise-free as possible. One should also be concerned with sensor complementarity, rather than emphasising on sensor redundancy. These aspects should be considered at the source level to alleviate the pre-processing of the information. On the other hand, the sample cycle should be small enough to be contained within the time over which faults in the machine develops, and input frequencies should be carefully selected to achieve the desired monitoring capabilities.

After the data has been acquired at the source level, it passes through to the pre-processing unit for digital conversion and proper manipulation. At this stage spectral analysis, correlation, image processing, time averaging, thresholding, and dimension reduction techniques are implemented based on the data at hand. The processed data is then pushed through to the fusion centre and routed according to the level of fusion sought, i.e. *raw data*, *feature*, or *decision* level fusion. Thus, the data will reach the data alignment stage or the post-processing stage accordingly. No single fusion technique has been proposed, selection must be made depending upon the application. The information available and the level of inference sought would clearly determine the "most likely to work" method. Table 1 exemplifies some applications and some of the most commonly recommended fusion methods. The fusion process could be applied considering a unique Condition monitoring system, combining different sets of data, or considering several Condition monitoring systems, combining different measurements.

For condition monitoring purposes, the output from the fusion centre should contain explicit information that can lead towards the health assessment of the machine. A faulty/not-faulty type signal, with a range of in-betweens, can certainly aid in the decision making of the plant supervisor. This sort of information can be derived from the best estimate, based on decision logic, in the form of a probability measure.

Fusion method	**Application**
Best-fit functions, Kalman filter	Combine signals to enhance information
Neural network	Signal interpretation
Logical filters, Image algebra	Image processing/segmentation
Markov random field, Simulated annealing	Image processing
Extended Kalman, Gauss-Markov	Feature extraction
Classical inference	Decision making
Bayesian theory	Decision making between hypotheses
Dempster-Shafer	Decision making with belief intervals
Evidential reasoning	Decision making with belief intervals
Fuzzy logic	Handle vagueness
Expert systems	Pattern recognition

Table 1. Data Fusion techniques and applications.

For the sake of illustration, consider two transducers strategically placed to acquire sensible vibration information based on the health of a machine. Further, assume that only two hypotheses are considered: Fault, *H*, and no-fault, $\overline{H} = 1 - H$. If a red/green light signal is required, the combination process should be done based on previous knowledge: i.e. decision fusion must be called to do the job. One of the most widely used techniques, at this level of fusion, is the Bayesian probabilistic reasoning. This is preferred over other methods when a hard decision output is required. Of course, other approaches could be chosen at this stage according to the type of uncertainty in the measurands (e.g. possibility, plausibility, belief, vagueness). A mayor drawback of this approach is that large amount of data would have to be processed in order to obtain the probability inputs. The Bayesian reasoning searches for a-posteriori probability of a hypothesis based on the signal output, that is:

$$P(H/S) = \frac{P(H)P(S/H)}{P(H)P(S/H) + P(\overline{H})P(S/\overline{H})} \qquad \text{Eq. (1)}$$

where *P(H)* is the a-priori probability of the hypotheses *H*, which varies according to the technique used and the machine being inspected (experience being the best guidance). *P(S/H)* is the conditional probability of measuring a specific output signal *S* given hypotheses *H* is true (a fault is present). For the case of two statistically independent sensors, Eq. (1) can be re-written as:

$$P(H/S_1 \cap S_2) = \frac{P(H)P(S_1/H)P(S_2/H)}{P(H)P(S_1/H)P(S_2/H) + P(\overline{H})P(S_1/\overline{H})P(S_2/\overline{H})} \qquad \text{Eq. (2)}$$

where $P(H/S_1 \cap S_2)$ is the a-posteriori probability of occurrence for hypotheses H given the combination of the signals, S_1 and S_2. The a-posteriori probability will have to be computed for the two sensors: i.e. $P(H/S_1 \cap S_2)_1$ and $P(H/S_1 \cap S_2)_2$. Decisions would be made based on the highest support.

EXAMPLES

Example 1 Knowledge based decision fusion

In complex systems we make decisions based on measured parameters, but we relate those to knowledge about the way the systems operates. In manufacturing systems, for example, operational faults account for about 70% of failures. Rapid diagnosis is critical for improving the availability and productivity of the manufacturing system.

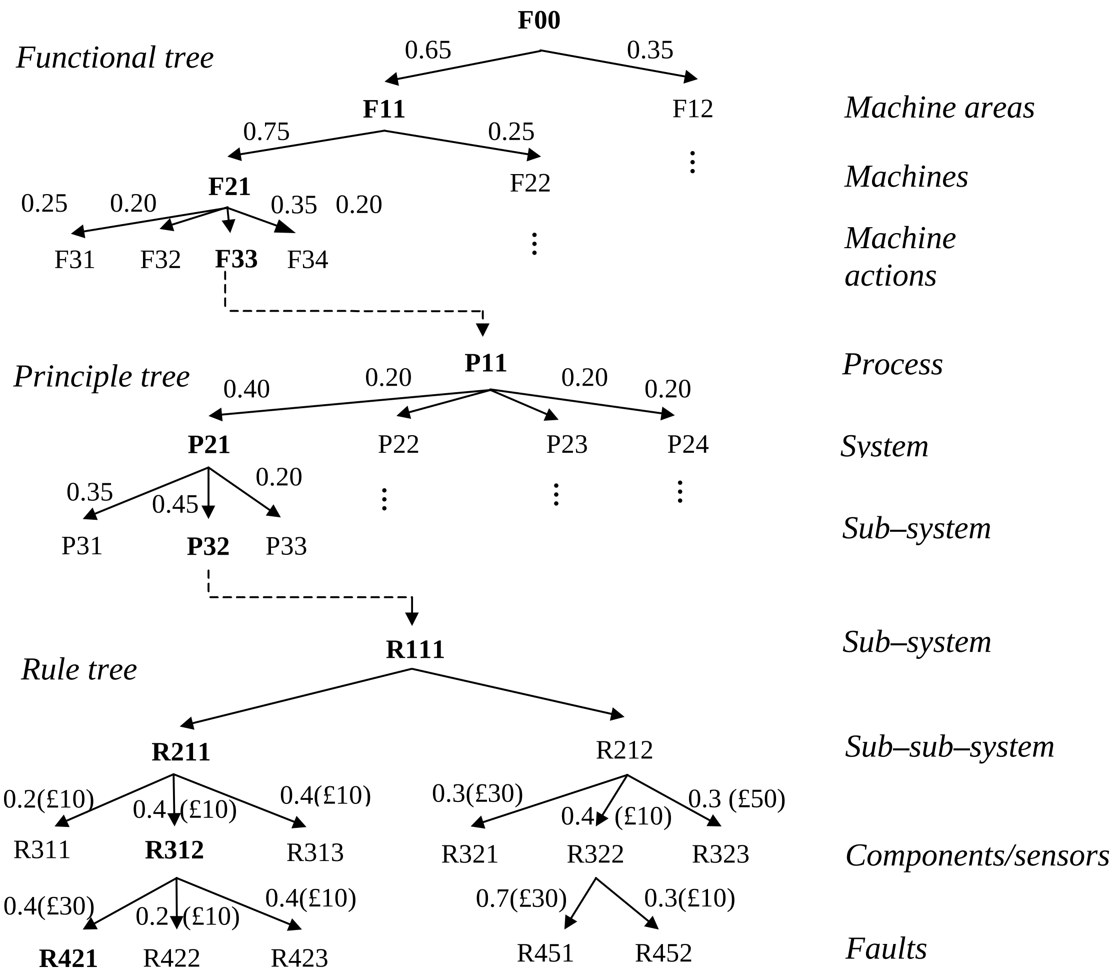
Diagnosis of complex systems is challenging because there are many different faults, and training is likely to be forgotten before it can be applied. Hierarchical diagnosis models, based on fault tree analysis, logical control and sequential control can be built around the operation of the Programmable Logical Controller (PLC). With these models working together, the operational faults of a manufacturing system can be diagnosed completely. The models have been successfully applied to a PLC controlled flexible manufacturing system and have achieved good results [25].

The model combines knowledge about the intended operating procedure with measured inputs from the normal automation sensors. The stage of the programme indicates the broad area of the fault, and the status of the measured inputs localises the solution further. In the example shown in figure 3, a system fault in a flexible manufacturing system (FMS) is traced:

- In the functional tree, we first establish that the FMS has failed because of a machine tool (F11); the tree further establishes that this is a PFZ1500 milling machine (F21); this has failed during the machining process (F33).

- According to the principles of operation of the machining process (P11), the highest probability lies in a spindle failure (P21: 0.4) and that, in this case, the most likely fault is the spindle motor (P32: 0.45).

- The rule tree analyses the potential faults in the spindle motor and their cost weighted risk. Here several potential faults are compared, and the most likely ones are investigated: a fault could exist in the mechanical drive system (R211) or in the control circuit (R212). A first likely fault is a high temperature cut out (R312) caused by a blunt tool (R421). Other likely faults are investigated in order of probability until the fault is found.



Functions
F00: FFS-1500-2 FMS
F11: Machine Tools
F12: AGV
F21: PFZ1500 FMC
F22: KBNG85 MC
F31: Tool Change
F32: Tool-head Change
F33: Machining Process
F34: Hydraulic Drive

Principles
P11: Machining Process
P21: Spindle
P22: X-axis
P23: Y-axis
P24: Z-axis
P31: Spindle Feed
P32: Spindle Motor
P33: Spindle Transmission

Rules
R111: Spindle Motor
R211: Motor Drive
R212: Control Circuit
R311: Mechanical Parts
R312: Motor Temperature
R313: Motor Connection
R321: Circuit Connection
R322: Power Connection
R323: Control Amplifier
R421: Tool Edge
R422: Cooling System
R423: Feed Load
R451: Fuse
R452: Power Switch

Figure 3: A diagnostic reasoning procedure for a machine tool [25]

Example 2 Condition monitoring over Fieldbus with intelligent sensors

A Fieldbus network was constructed at the University of Manchester to demonstrate the use of smart sensors in condition monitoring. A PC was programmed to act as a combined bus arbitrator and CM controller, and another as a remote node and intelligent sensor. 50% of the Fieldbus bandwidth was deliberately occupied by the continuous transmission of simulated time critical control variables. On the Fieldbus between the two PC's a field tap was provided to permit a third PC to access the Fieldbus and transmit the data to an Ethernet link to an Internet server. The server provided world-wide real-time access to the condition monitoring of an induction motor in the Manchester laboratories and the functioning of the intelligent sensor as the motor's condition was changed on line. Figure 4 shows a schematic of the demonstrator system, and figure 5 shows the web page output.

The function of the CM controller was to implement the monitoring strategy. In overview, this involved requesting information from the intelligent sensor, interpreting this information, and issuing messages as necessary for consumption by the management information systems that would in reality be present on the same network. Specifically, the monitoring strategy was defined as follows:

- routinely request a condition status (i.e. a green, amber or red traffic light) from the intelligent sensor;
- if status is green, record status and time stamp, then wait 60 seconds until next status indicator is required;
- if status is amber, record status and time stamp, then request and record data summary, then reduce subsequent monitoring interval to 15 seconds;
- if status is red, record status and time stamp, then request and record full data transmission, then reduce subsequent monitoring interval to 15 seconds and issue a warning message onto the network for consumption by the management information systems.

There are numerous ways in which this monitoring strategy could be changed or refined. The system demonstrated 'on-request' communication of condition monitoring information over a Fieldbus network which was being used for the simultaneous transmission of time-critical data. In terms of the intelligent sensor, the prototype included simple signal processing:

- sensing, filtering and amplification of vibration acceleration data;
- sampling and digitisation;
- calculation of RMS level and frequency spectrum (FFT);
- comparison of processed output with thresholds;
- determination of the current status;
- on request from the condition monitoring controller, transmission of the status, time stamp, data summary or full FFT as necessary.

Example 3 Advanced signal processing algorithms in an intelligent sensor

Analytical techniques can accentuate condition monitoring information by manipulating the data from measurements. In rotating and reciprocating machines it is common to use software or hardware to convert a time series of vibration data into the frequency domain. This has limitations in non–stationary signals because transient events are lost in the averaging. Time-frequency representations permit the simultaneous representation of a signal's time, frequency and amplitude on a per cycle or per revolution basis. [26]

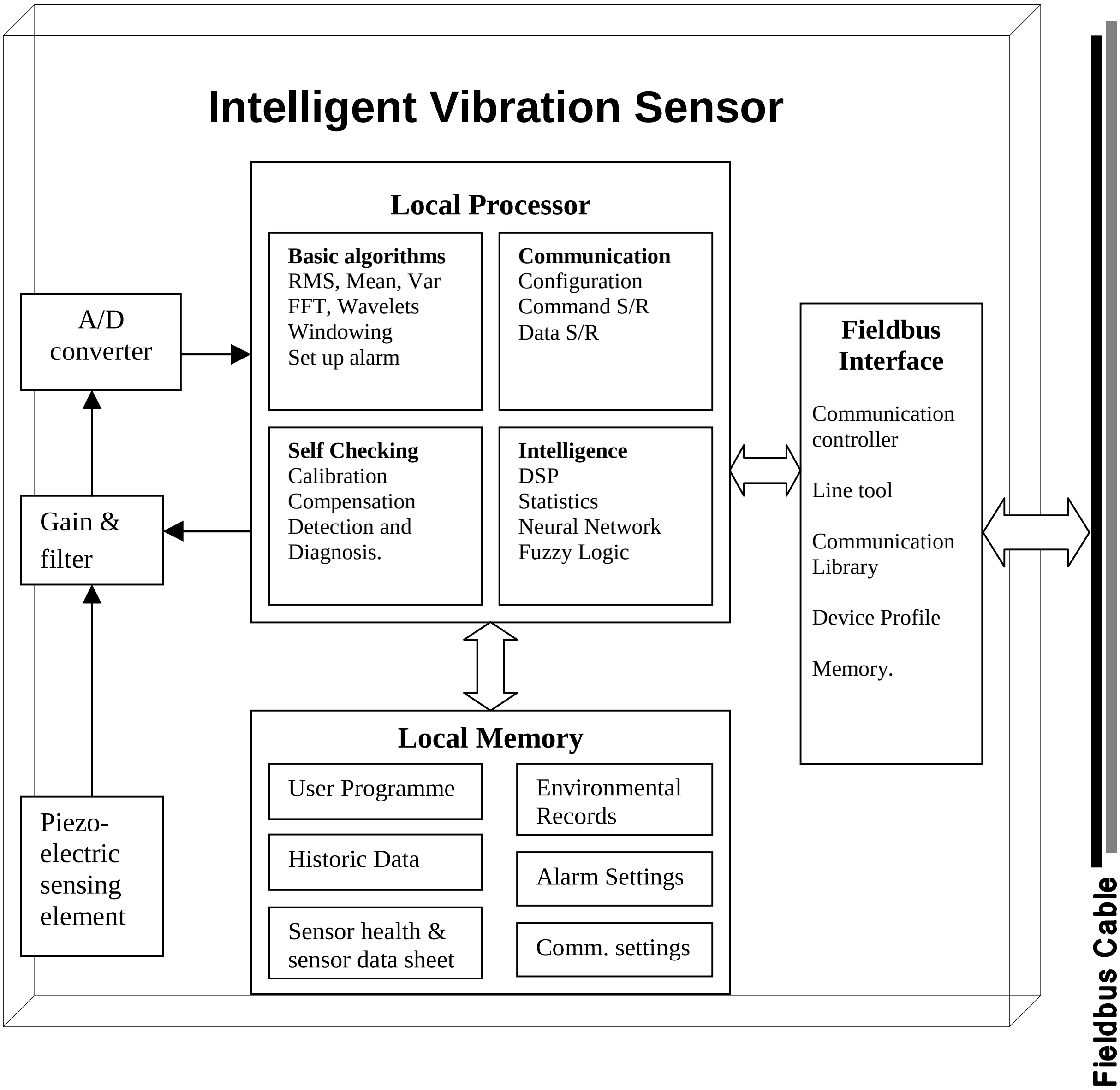


Figure 7: Schematic of the demonstrator Fieldbus–based smart sensor

Time-frequency methods are particularly useful in CM because many common machine faults give rise to transient vibration or electrical symptoms which are superimposed upon a continuous periodic waveform. The transients themselves may occur from impacting, stiffness variation around a cycle, or asymmetric magnetic effects. With the ability to interpret the output of advanced signal processing techniques such as these, comes the ability to incorporate them within a stand-alone microprocessor system such as a smart sensor.

The example shown in figure 6 demonstrates the characterisation of a diesel fuel injector. Its characteristics are hard to identify in the noisy environment of the engine when using the time domain or frequency domain alone. In the time–frequency plot, however, it is possible to detect the timing events, including the opening and closing of the injector needle, the onset and duration of combustion, and the peak acceleration level, which is well correlated with the maximum pressure in the cylinder. The time–frequency plot has sufficiently high resolution to identify faults in injection and timing.

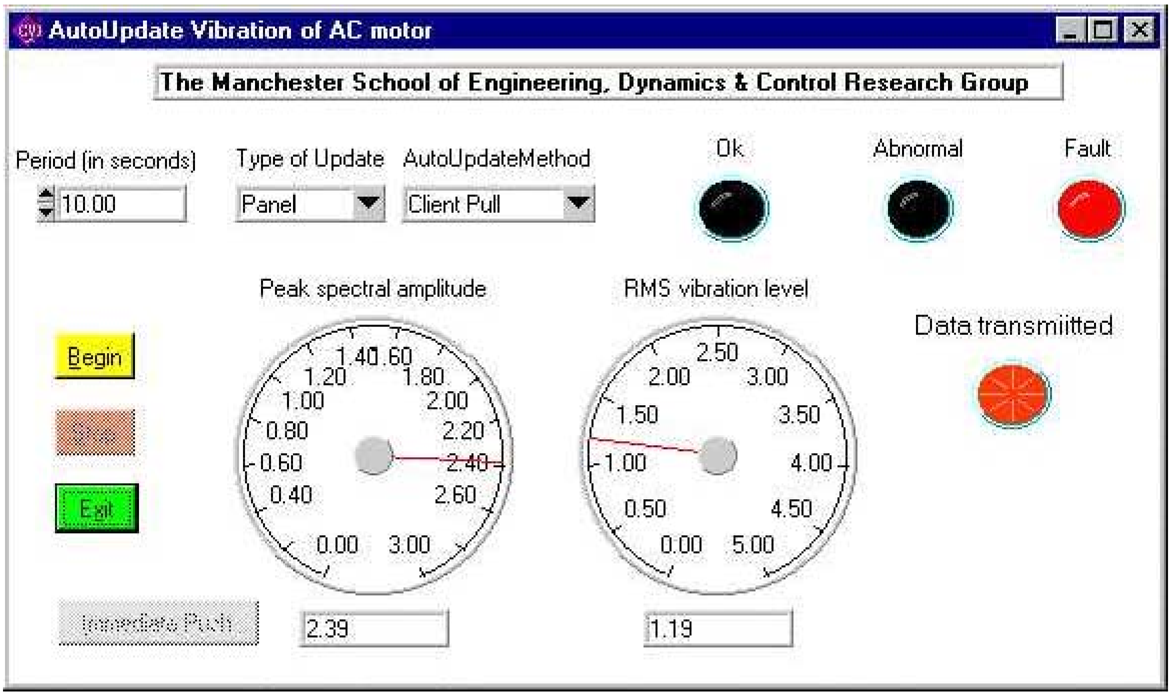


Figure 5: Web page output from the demonstrator smart sensor

CONCLUSIONS AND FURTHER WORK

Data fusion is widely used by scientists of many disciplines. There are many individual examples of successful application. There is a need, however, for a clear overall strategy with which to define and classify the problem and hence select fusion techniques.

A picture is emerging of a flexible strategy, which incorporates a number of steps. This needs to be refined by encapsulating expertise, from a variety of sources, which defines the patterns and interconnection between solution steps, and matches the solution to the previously defined problem characteristics.

Data fusion has been used in many disparate fields, and must be regarded as a superset of data processing algorithms, parts of which are well classified and documented for particular fields and applications. The difficult part is to generalise the strategy.

A necessary prerequisite for an engineering solution is a full statement of the problem: its definition and classification. This enables a specification to be drawn up and a solution devised. Indeed, it is often agreed that the problem definition is half the battle.

In data fusion, individual problems have received thorough treatments. It is not easy, however, to approach a new data fusion problem. Even relatively experienced users of data processing methods have difficulty selecting the best approaches, and the expertise used in such selection is far from uniform. These issues have been characterised in the “application pull” from industrialists in the UK Faraday INTErSECT programme [27].

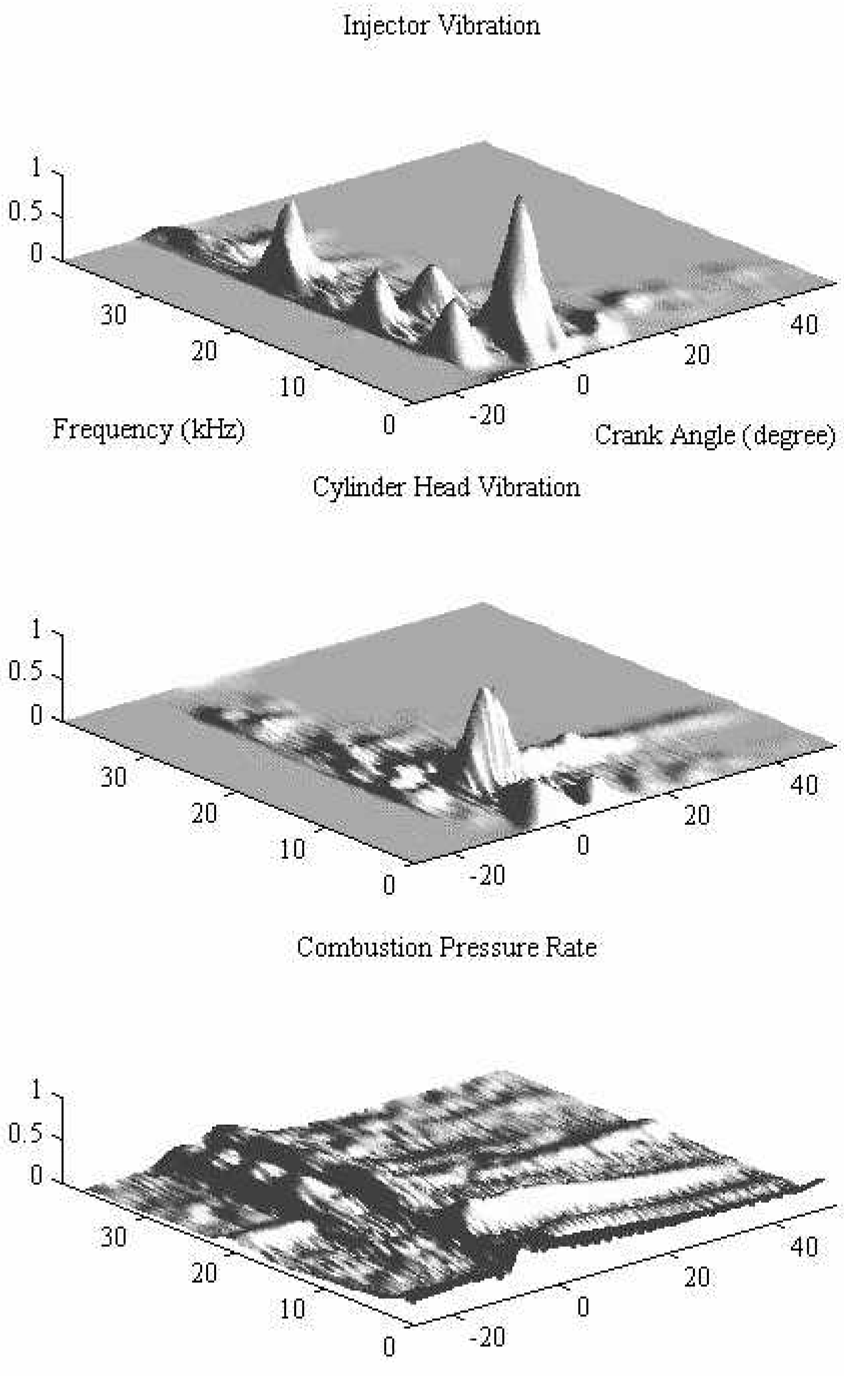


Figure 6: Characterisation of a diesel fuel injector from vibration and cylinder pressure, displayed in time–frequency plots
Engine FSD425 operating at 59.7Nm and 2043 rev./min.

The limitations lie in the focus, to date, on particular advanced applications and specific techniques, combined with the understandable reluctance to report negative results. A generic framework is required which allows selection of best practice methods based on problem and required solution characteristics. Details of the content of the fusion map are already established.

The knowledge of a range of academic and industrial practitioners are currently being mapped and best practices recorded as case studies. Strengths of particular techniques and architectures will be cross-referenced to problem characteristics, particularly in the field of condition monitoring. As an adjunct, known hazards will also be clearly mapped. An underlying and fundamentally generic approach will be derived.

It is the pattern and interconnection which is the subject of current work. The map and its algorithm can be tested in three ways:

- Demonstration of the methodology in application to already known case studies, which should confirm some decisions but offer alternatives or even challenges to others.
- Application of the methodology to new problem data.
- Application of the methodology to define *preferred* data characteristics, i.e. use data fusion as a part of the design process.

The last of these will be achieved by collaboration with our academic partners at the University of Warwick, whose experience lies in the measurement of fluid flow using optical methods. The industrial partners have a range of experience in measuring combustion progress, with a variety of instruments. The fusion map is currently being used in the design process of in-cylinder combustion temperature mapping measurement systems and in subsequent interpretation of the data.

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